A Work Project, presented as part of the requirements for the Award of a Masters Degree in Finance from the Faculdade de Economia da Universidade Nova de Lisboa.

Alpha Generation with Twitter's Daily Momentum

Miguel Maria Borges Leitão Leal da Costa; Student Number 14826

A Project carried out on the Financial Markets course, with the supervision of:

Professor Afonso Fuzeta Eça

January 8th 2016

ABSTRACT

This thesis does not set out to focus on the dynamics relationship between Twitter and stock prices, but instead tries to understand if using relevant information extracted from tweets has the power to increase investors' stock picking ability, and generate alpha in portfolio's choice relative to a benchmark. Despite the short period analyzed, it gives promising results that the sentiment analysis performed by Social Market Analytics Inc. applied to an equity portfolio, is able to generate positive abnormal returns, statistically significant in and out of sample.

Keywords: Market Sentiment, Sentiment Analysis, Twitter, Stock Picking.

Acknowledgments

I am very grateful for the supervision of my advisor Professor Afonso Fuzeta Eça. I would like to thank Dr. John Fox and Dr. Jeff Blaschak from Social Market Analytics Inc. for all the support provided. I am very thankful for the invaluable support of my good friend João Cunha.

I. Introduction

While a single lost word might contain a negative or positive sentiment, two words may have several interpretations, and Twitter works has a vast storehouse of public mood that can be used to access what users are feeling, with 320 million active users sharing 1 billion tweets – short messages up to 140 characters – every day. Twitter offers “an unprecedented opportunity to study human communication and social networks,” (Miller, 2011). The prediction of the financial markets is a multibillionaire industry and many companies, with more or less success, have been trying to do this since the first stock markets exchange were found, which has been a true challenge not only to investors but also to researchers over the years. The study of social mood has been a growing subject in the prediction of financial markets.

On the 23rd April, 2013 the Associate Press, a news’ agency founded in 1846 suffered an e-crime. The hacker was able to publish a false statement through Associate Press’s Twitter’s account stating that a terrorist attack on the White House had possible happened. The S&P 500 index, in 4 minutes, suffered a loss of 136 billion dollars. This amount was restored with the same velocity as it was lost, when the situation was taken care of. Just as it happened with an index, so it can also happen with all companies quoted on the stock market. More recently, a similar situation happened when Financial Times published an inaccurate Tweet about the decision of the European Central Bank to leave interest rates unchanged, which made markets to stir.

The price of a stock quoted on the stock market tends to fluctuate with the information available on the market, and with this, it is easy to understand that an investor with the ability to detect the sentiment related to a stock faster than the market, will be able to better maximize his returns. Hence, there is the need to be aware of the information available, which is mostly released in the form of news.

When working with financial markets we can understand that it is through social media platforms such as Twitter that journalists, private investors and all financial and non-financial companies launch their information to the market in a quickly and concise way. By analyzing millions of tweets it is possible to transform text into data organized by entities, themes and concepts that after careful treatment allow us to obtain the sentiment related to a company, to an industry, to a political party or a country. This way, it is possible to detect what crowds are feeling. A good example of a company being successful in predicting future price movements is the Cayman Atlantic Hedge Fund, that presented its investor with Sharpe Ratios higher than 1 over the last 3 years.

A lot of doors were closed while trying to find how to work on this subject, until I met Dr. John Fox from Social Market Analytics, Inc. (SMA). SMA produces a family of metrics, called S-Factors that were designed to capture the signature of financial market sentiment. SMA applies these metrics to data captured from social media sources to estimate sentiment for indices, sectors, and individual securities. More specifically, these metrics are estimated from analyzing tweets that are then converted into actionable indicators.

SMA provided data for sentiment and volume. This company has patents on their process and for that reason this thesis does not discloses information about specifics of the data that was used, and is only be able to comment SMA's process of sentiment analysis from results achieved.

Moving forward in the analysis, the strategy that was built uses sentiment jointly with volume, in order to assess if there is an upward or downward pressure for individual stock prices to fluctuate. The strategy uses sentiment factors in order to determine, not only when should an investor take a position in a particular stock, but also if the direction of the position should be long or short according to a positive or negative sentiment, respectively. The volume factor is used as a filter that imposes a limit on the number of stocks in which one should invest, because this strategy tries to only invest in stocks with robust sentiment factors extracted from a large number of tweets.

After building an investment strategy with factors provided by SMA, regression analysis were performed in order to understand if the strategy has a statistical significant alpha, in and out of sample. The additional return that is not explained by the market is called abnormal return, or alpha, which results from the portfolio's manager ability to exploit opportunities arising on the market, and is frequently used as measure for assessing an active manager's performance, in relation to market returns. The conception and focus on alpha comes from the fact that during the twentieth century, stock investment managers were not making more money than investors who simple invest in the overall market. Since a positive and significant alpha allows concluding that looking at information from tweets increases the stock picking ability of an investor who is able to correctly use it, this work's investigates if strategies using tweets' sentiment signals yield a robust alpha. Other metrics are also studied to prove this strategy is as robust as possible.

The rest of the work follows this path: Section II reviews the relevant literature on this topic. Section III describes the specificities of the data used. Section IV explains the methodology taken to perform the strategy and different techniques applied to better understand the regressions' results. Section V presents and discusses the results. Section VI concludes this work.

II. Literature Review

Primarily, this thesis tries to establish a link with the literature that approaches findings on market sentiment through social media platforms.

"In models of investor sentiment on stock market prices, uninformed traders rely on various information sources in forming their beliefs. In equilibrium, their beliefs, albeit noisy, influence prices" (Sheng & Oh, 2011). This work tries to reinforce what other researchers have studied, regarding subjects related to news that are spread in social media platforms, their relevance and usability for portfolio managers. Also, it tries to prove that stock discussions are not always noise, as Antweiler & Frank, 2004 proved.

The process of studying if Twitter has the power to exploit stock picking ability starts with the sentiment analysis applied to tweets. After some research, one can find that examples of pioneering uses for sentiment analysis are plentiful. Sentiment analysis is being used as a tool in new industries and with different objectives such as preparing for and avoiding scandals, in other words, taking a proactive position vs reactive position - LEGO and Shell scandal 2014; or using healthcare records to improve practices and process efficiency in healthcare services - Arizona Universtiy' study on Sentiment Analysis of Data Collected from Social Media for Improving Healthcare.

Different methods can then be employed to classify data, and researchers have been actively investigating the problem of automatic text categorization. After developing the classifiers, researchers need to train them in order to evaluate and improve their effectiveness (Sebastiani 2002). From the research that was done, it can be understood that there are a few key challenges for sentiment analysis in order to make a sentiment analysis as robust as possible: 1 - “While machine do analytics, humans do analysis” by Anjali Lai – improving the final outcome of a sentiment analysis is only possible with years of experience; 2 - The analysis must treat carefully the accuracy of numbers in an environment where it is possible to correlate everything against everything – a good example is the Bank of England’s attempt to analyze whether Twitter could help predict a bank run prior to the referendum for Scottish independence. A group of data analysts at the bank decided to search for terms that showed fears over financial stability, linked to Scotland and the referendum. They built a system that would analyze Twitter in real time, looking for signals of bank runs by searching for key terms, like "runs" or RBS - Royal Bank of Scotland. At the same day of the voting, the Minnesota Vikings and the New England Patriots were playing on a Sunday evening and the reason the model showed an increase in activity was due to fans tweeting about “runs” and “RBs” – which refers to running backs, not The Royal Bank of Scotland.

Others researchers were interested in potential applications of Twitter information rather than finance. Tumasjan et al. (2010) analyzed Twitter messages mentioning politics information related and found that the number of tweets is able to reflect voters’ preferences. Also, Asur and Huberman (2010) tried show how social media can predict future outcomes by predicting revenues of movies, and proved there is a strong correlation between the attention given to a certain topic and its ranking in the future.

Another relevant issue that must be taken into account is the fact that one may argue that individuals exploit social media tools such as Twitter by disseminating misleading and speculative information to investors. However, previous research shows that the information on Twitter can help investors in their investment decision, and leads to the conclusion that Twitter can play a role in making the market more efficient (Bartov, Faurel and Mohanram, 2015).

"The three distinct characteristics of these tweets, succinctness, high volume and real-time, greatly facilitate the diffusion of investing information in the community" (Oh and Sheng, 2011). With the dramatic increase in the use of social media, fact is that it transformed the capital markets in a way that firms use it to communicate with their investors' base in a timely and cost effective way, and investors have a fast channel to access information, share their information and insights about markets. Researchers found that the aggregate information contained in individual tweets helps to predict firms' quarterly earnings (Bartov, Faurel, Lucile and Mohanram, 2015). This study takes us to another type of analysis, and to believe in the concept of Wisdom of Crowds that refers to a phenomenon first observed by Sir Francis Galton, who studied the fact that a large group of problem-solvers thinking independently often makes a better collective prediction than that produced by experts, no matter how brilliant they are at solving problems:

"In 1907, Sir Francis Galton asked 787 villagers to guess the weight of an ox. None of them got the right answer, but when Galton averaged their guesses, he arrived at a near perfect estimate. This is a classic demonstration of the 'wisdom of the crowd', where groups of people pool their abilities to show collective intelligence."

A more broadly study was done (ECB 2015), which quantifies the effects of online bullishness on international financial markets, by reporting the frequency of appearance of the terms bullish and bearish in Twitter content and Google over time. Their results support the investor sentiment theory (by De Long et al., 1990a), and suggest that Twitter bullishness may provide a useful and simple investor sentiment index. Not only leading indexes in the US but also in UK and Canada, and a very modest predictive value over Chinese market. Because people pay more attention to negative than positive news, a rational way of human thinking (Luo, 2007), leads investors to believe bullish sentiment to have a lower predictive accuracy than that of bearish sentiment. This thesis is able to understand that in general positive news/sentiment yield better returns rather than when looking at negative news/sentiment.

III. Data

SMA uses actionable intelligence from social media data by filtering out the noise to deliver clean data on sentiment for financial markets. More specifically, it produces a family of metrics, called S-Factors, designed to capture the signature of financial markets sentiment. They provided a set of data with daily frequency ranging from the 1st August 2013 to 22nd September 2015, with factors for sentiment and volume over all stocks on the S&P 500 index.

These daily sentiment and volume factors are captured before the market opening – at 9.10 AM, US Eastern Time - and before the market close – at 14h55 PM, US Eastern Time - which allows the investor to take positions before the opening or closing of the market.

S&P 500 Index can be considered an excellent market to apply this study since the United States has the highest concentration of Twitter users in the world (Fiegerman, 2012; ECB, 2015) which allows us to believe that Twitter is more present in peoples' lives than in any other country.

SMA has a three stage process to mine sentiment factors (S-Factors), not only from Twitter but also from StockTwits messages, composed by three stages: 1 - The Extractor: where the process starts by extracting all signals for designated financial terms and symbols with no filter; 2 - The Evaluator: where all tweets are analyzed for financial relevance – indicative tweets - using proprietary natural language processing algorithms. In this sample, the number of indicative tweets related to a stock in a given day ranges from 1 to 2520; 3 - The Calculator: which determines the sentiment signature for each stock using a sentiment dictionary adjusted for performance in the financial market domain.

This process is done by gathering information into time period buckets based on the moment at which tweets were made public. Sentiment level for each word analyzed from a tweet is obtained from SMA's sentiment dictionary, which has over 18,000 words and 400 two-word phrases that have content and sentiment levels of relevance to financial market activity.

A normalization and scoring process calculates the final sentiment measures. Raw sentiment level (Raw-S) is the simple aggregate of sentiment levels of all indicative tweets' related to a stock, captured during the prior 24 hours, which is normalized to S-Score factors. S-Score is the normalized representation of a sentiment time series, over a look back period created to establish a common scale according to a local mean and standard deviation. Positive S-Scores are associated with favorable changes in investor sentiment, while negative levels are associated with unfavorable changes – see table 1.

Table 1 – Sentiment Regime

S-Score	Market Sentiment Regime
> 3	Extreme Positive
> 2 and < 3	High Positive
> 1 and < 2	Positive
> -1 and < 1	Neutral
< -1 and > -2	Negative
< -2 and > -3	High Negative
< -3	Extreme Negative

In order to run regressions with the portfolio's returns and test the statistical significance of the alpha, Fama-French Factors with daily frequency were obtained from Kenneth R. French data library, as the series for momentum factor. The momentum factor added to Fama-French factors completes the Carhart Four-Factor Model.

IV. Methodology

In this section it is explained the investment strategy and outline some tests that were done in order to access if the strategy has a statistical significant alpha.

The strategy takes into account both sentiment and volume factors, one on top of the other. It is reasonable that an investor should focus on stocks with relevant positive and negative sentiment signals, which most probably lead to higher levels of returns. For this reason, our base strategy focuses on high positive and negative sentiment. Firstly, the strategy takes long positions in all stocks of the S&P 500 index showing a S-Score higher than 2.5 (intermediate level of high positive sentiment) and short positions in stocks with average S-Score below -2.5 (intermediate level of high negative sentiment).

Secondly, the strategy looks to the volume of indicative tweets, from where sentiment signals were extracted to each stock, and ranks stocks according to the number of tweets that were published about them. This filter's objective is to not only narrow the number of stocks to invest in, but also to make sure the sentiment being captured derives from a large sample of tweets, providing robustness to the analysis. In our base strategy we choose the top 15 stocks with the highest number of tweets, since it seems to be a reasonable number. These strategy uses signals collected before the market close, allowing the strategy to consider market closing prices as entry prices, and positions are held until the end of the next trading day. In order not to leverage the portfolio, daily returns are divided by the sum of long and short positions.

The reasoning behind the filter volume is similar to the S-score, and a simple concept to grasp, as the volume of tweets about some news or article of a company helps identify which tweets/news will have a more meaningful impact in sentiment – and therefore performance – of a stock. The final goal of these two filters is to only invest in stocks with robust sentiment factors extracted from a large number of tweets.

To access if this strategy yields positive and significant alphas, this work tries to identify and quantify the factors that determine the alpha of the strategy by utilizing historical data in a multivariate regression, and the statistical likelihood that both factors and alpha are different from zero, measured by a relevant t-statistic. This work focus on Fama-French model, rather than CAPM, since the Fama-French explains better the variation observed in realized returns as it often exposes the fact that a positive alpha observed in CAPM regression is merely a result of exposure to HML and SMB factors rather than actual stock picking skills. Portfolio's returns were also regressed against the

Carhart Four-Factor model, which adds the momentum factor to the Fama-French model.

The order of importance that was followed to better understand the alpha was to, first run a t-test on portfolio's return since it allows to statistically reject the hypothesis that they are zero:

$$t = \frac{(x - \mu)}{\text{Standard Error}}$$

$$\text{Standard Error} = SE = \frac{\text{Standard Deviation of Portfolio Returns}}{\sqrt{Sample\ Size}}$$

Secondly, check if the alpha from both Fama-French and Carhart models' regressions with portfolio's returns is positive and significant, in and out of sample.

Finally, it is analyzed the Information Ratio (IR). While the Sharpe ratio assesses manager's performance relative to risk taken, IR measures the ability and consistency to generate excess returns relative to a benchmark, computed this way:

$$\boldsymbol{Information\ Ratio} = \frac{Annualized\ Portfolio's\ Returns - Annualized\ Benchmark's\ Returns}{Annualized\ Standar\ Deviaton\ of (Portfolio's\ Returns - Benchmark's\ Returns)}$$

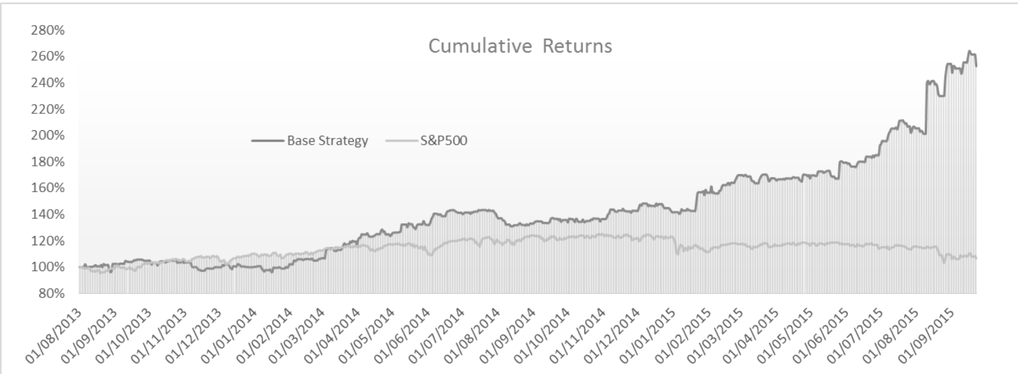
The information ratio provides a good measurement on portfolio manager's skills and consistency relative to a benchmark.

V. Results

This section attempts to interpret the strategy's results. A sensitivity analysis is also performed on different outcomes of the strategy resulting from different inputs – S-Score, ranking of stocks by tweets volume and look back period.

Since our goal is to prove that the strategy is able to generate alpha, we do not take into account transaction costs. With an S-Score of 2.5/-2.5 as a filter for sentiment with 1 day lag, and 15 stocks as a filter for volume, the base strategy yields a Sharpe ratio of 1.7198 with an annualized return of 32.68% and 19.00% annualized volatility over the 3 years' period being analyzed, compared to the S&P500 index, our benchmark, which yields a Sharpe ratio of 0.5448 with an annualized return of 7.08% and 12.90% annualized volatility. Graph 1 plots the cumulative return of our base strategy, and the cumulative return of the S&P 500 index during the period in analysis.

Graph 1 – This graph plots both cumulative returns of our base strategy and S&P 500 during the period being analyzed – 1/08/2013 to 22/09/2015.



The t-test done on portfolio's returns is 2.98, which tells us that our returns are statistically different from zero. The next step was to regress the portfolio's returns on Fama-French 3 Factor model (table 2.1).

Table 2.1 - This table shows the coefficients, alpha and their significance, of the regression of the entire sample of our portfolio's returns with Fama-French 3 factor model.

FF Regression	HML	SMB	MKT	Alpha
Coefficient	0,1938	0,0501	0,6009	0,1659%
t-statistic	1,2617	0,4041	8,3740	2,8785

The fact that the alpha is significant (t-statistic > 1.96) indicates a daily outperformance of 0.1659% with regards to Fama-French model. From the table above, we can see that all 3 factors are positive, but only the market beta is significant. This positive market beta means that returns are explained by the market, and one possible reason might be due to the volume filter used in this strategy since Google, Facebook, Amazon and Apple are examples of stocks that have a higher volume of tweets compared to other stocks, and represent a relevant share of the market.

Table 3.1 - This table shows the coefficients, alpha and their significance, of the regression of the entire sample of our portfolio's returns with the Carhart model.

Carhart	MOM	HML	SMB	MKT	Alpha
Coefficient	-0,3201	-0,0637	0,0365	0,6280	0,1706%
t-statistic	-2,8852	-0,3606	0,2963	8,7359	2,9776

Regarding the regression with the Carhart model, which adds the momentum factor to the 3 factor model, both market beta and alpha are slightly higher and significant when compared to Fama-French results (table 3.1). The t-statistic of alpha indicates that the portfolio daily outperforms the Carhart model by 0.1706%. We can also see that the momentum factor is significant but negative. One possible reason for the negative beta of momentum can be that we are going long/short in stocks with good/bad momentum on Twitter sentiment, but these stocks in general have performed badly/well in the past. The fact that we are using daily data, and the Carhart model takes into account monthly momentum, is a possible reason to explain the apparent negative correlation between the two factors, given that in this strategy the idea is to take advantage of very short term sentiment changes – daily Twitter momentum.

Since the momentum factor is significant, we are not going to analyze the Fama-French model. Instead will present regressions done out of sample with the Carhart model, for the 2nd half and last 6 months of the sample - tables 3.2 and 3.3 respectively.

Table 3.2 - This table shows the coefficients, alpha and their significance, of the regression of the 2nd half of our portfolio's returns with Carhart model.

Carhart	MOM	HML	SMB	MKT	Alpha
Coefficient	-0,3715	-0,1063	-0,0126	0,7048	0,2787%
t-statistic	-2,2576	-0,3963	-0,0659	6,8910	2,9906

Table 3.3 - This table shows the coefficients, alpha and their significance, of the regression of the last 6 months of our portfolio's returns with Carhart model.

Carhart	MOM	HML	SMB	MKT	Alpha
Coefficient	-0,7515	-0,6385	0,0114	0,7054	0,3890%
t-statistic	-2,6588	-1,3360	0,0308	4,0584	2,4654

Regarding alphas, and taking into account that we are looking at a 3 years period, the fact that both in and out of sample analysis show a positive and significant alpha proves that, with a proper sentiment analysis, such as the one implemented by Social Market Analytics, an investor is able to improve his stock picking ability. Regarding the coefficient of determination (R^2), which tests the goodness of fit of the model, as expected it is always low (<16%), since we have positive and significant alphas.

A sensitivity analysis is now going to study how different inputs impact our results. In short, it was found that the best way to build a strategy with Twitter's signals is to take into account the sentiment factor yielded for the day, and consequently taking positions before the market close and hold them until the end of the next trading day (1 day lag) – results on table 4.1. By looking at table 4.2 and following analysis, it is possible to understand that considering the average of the sentiment factor during a look back period, for example, the day before (2 days lag) does yield positive but poorest results compared to 1 day lag – results on table 4.2. When looking at the average of the sentiment factor with 3 days lag, the strategy loses all its Sharpe Ratio, significance of returns and alphas.

Table 4.1 – This table presents a sensitivity analysis on Sharpe ratios using different sentiment signals and volume filters, with 1 day lag.

1 Day Lag	S-Score				
Volume Rank	1,5	2	2,5	3	3,5
5	0,4152	0,5028	0,6706	0,8732	0,6990
10	1,0690	1,2514	1,1991	1,3230	1,1217
15	1,0864	1,6477	1,7198	1,5608	1,1631
20	1,1022	1,3780	1,6286	1,5900	1,4891
25	1,1876	1,3035	1,6718	1,6846	1,4685
50	1,3008	1,0958	1,2892	1,3918	1,3912
75	0,9839	1,1226	1,0952	1,1560	1,2204

Table 4.2 - This table presents a sensitivity analysis on Sharpe ratios using different sentiment signals and volume filters, with 2 days lag.

2 Days Lag	S-Score				
Volume Rank	1,5	2	2,5	3	3,5
5	0,5630	0,3788	0,3555	0,2654	-0,6293
10	0,5978	1,0979	1,0210	0,7466	-0,3512
15	0,5926	1,3573	1,4975	1,0586	-0,4496
20	0,7342	1,2656	1,5034	0,9252	-0,6108
25	0,7922	1,0941	1,3456	0,7800	-0,5382
50	1,1828	1,3761	1,4398	0,6471	-0,0973
75	0,8839	1,3726	1,1526	0,9782	0,3378

From tables 4.1 and 4.2, we can see that Sharpe ratios are higher when using 1 day lag instead of 2 days lag. It can be concluded that sentiment factors are quite short term, which makes sense since Twitter reactions are usually very momentary.

Tables 5.1 and 5.2 show the t-test that was done to prove which inputs lead to a series of the portfolio's returns that are statistically different from zero. It is possible to see that different strategies with 1 day lag (table 5.1) have a higher number of inputs leading to portfolio's returns that are statistically different from zero, when compared with 2 days lag (table 5.2). T-tests results are also higher, and the higher the t-test the higher is the significance. This comparison of statistical significance of portfolio's returns with 1 day lag versus 2 days lag, is in accordance with previous conclusions from tables 4.1 and 4.2 regarding sentiment factor being short-term and Twitter daily momentum.

Table 5.1 – This table presents a sensitivity analysis for the statistical significance of portfolio's returns, using different sentiment signals and volume filters with 1 day lag. A t-test > 1.96 allows to statistically reject the hypothesis that portfolio's returns are zero.

1 Day Lag	S-Score				
Volume Rank	1,5	2	2,5	3	3,5
5	0,7188	0,8704	1,1608	1,5115	1,2100
10	1,8504	2,1660	2,0755	2,2900	1,9416
15	1,8804	2,8521	2,9768	2,7017	2,0132
20	1,9078	2,3852	2,8190	2,7522	2,5775
25	2,0556	2,2563	2,8938	2,9160	2,5419
50	2,2517	1,8967	2,2315	2,4091	2,4080
75	1,7031	1,9432	1,8958	2,0010	2,1125

Table 5.2 - This table presents a sensitivity analysis for the statistical significance of portfolio's returns, using different sentiment signals and volume filters with 2 days lag. A t-test > 1.96 allows to statistically reject the hypothesis that portfolio's returns are zero.

2 Days Lag	S-Score				
Volume Rank	1,5	2	2,5	3	3,5
5	0,9746	0,6558	0,6154	0,4593	-1,0893
10	1,0347	1,9005	1,7672	1,2924	-0,6079
15	1,0257	2,3494	2,5920	1,8324	-0,7782
20	1,2708	2,1907	2,6023	1,6015	-1,0572
25	1,3712	1,8939	2,3291	1,3501	-0,9316
50	2,0473	2,3819	2,4922	1,1201	-0,1683
75	1,5300	2,3759	1,9951	1,6932	0,5846

Since previous regressions showed a significant momentum factor, and taking into consideration that alphas are always positive, on tables 6.1, 6.2 and 6.3 we analyze the significance of alphas from regressions with the Carhart model, with 1 day lag.

Table 6.1 – This table presents a sensitivity analysis, using different sentiment signals and volume filters using 1 day lag, for the significance of the alpha computed from the regression of the entire sample of portfolio's returns with the Carhart model.

1 Day Lag	S-Score				
Volume Rank	1,5	2	2,5	3	3,5
5	0,5979	0,7825	1,2059	1,4547	1,1281
10	1,6718	2,0892	2,0571	2,0738	1,7464
15	1,6271	2,7816	2,9776	2,4460	1,7986
20	1,6223	2,2679	2,8274	2,5998	2,4725
25	1,8251	2,1645	2,9417	2,8624	2,4944
50	2,1519	1,8617	2,2220	2,3817	2,3642
75	1,4957	1,8572	1,7413	1,8785	2,1035

Every analysis that was done so far, including results from table 6.1, support our predictions on which inputs should be used. Also, table 6.1 reinforces that fact that 1 day lag's strategies show robust results regarding investment performance, and statistical significance of portfolio returns and alpha.

On table 6.2 and 6.3 you can see the significance of the alpha of two regressions made out of sample - for the 2nd half and last 6 months of the sample, respectively. Once again, only 1 day lag strategy is presented since the 2 days lag strategy yields positive alphas but with no significance. In a strategy with 3 days lag, all relevant indicator is lost.

Table 6.2 – This table presents a sensitivity analysis, using different sentiment signals and volume filters using 1 day lag, for the significance of the alpha computed from the regression of the **2nd half** of the portfolio's returns with the Carhart model.

1 Day Lag	S-Score				
Volume Rank	1,5	2	2,5	3	3,5
5	1,2559	2,0155	2,1113	1,7790	1,2811
10	2,1998	2,7670	2,9961	2,4149	2,1097
15	1,8957	2,5467	2,9906	2,3578	1,7737
20	1,5801	2,1240	2,6465	2,2564	2,4439
25	1,8734	2,2515	2,8039	2,9105	2,9435
50	2,5018	2,4064	2,5505	3,2284	2,9212
75	2,3913	2,7469	2,6439	2,3765	2,5259

Table 6.3 – This table presents a sensitivity analysis, using different sentiment signals and volume filters using 1 day lag, for the significance of the alpha computed from the regression of the **last 6 months** of the portfolio's returns with the Carhart model. (The last 6 months of the sample have less than 200 observations, which means that alphas are only significant if t-statistic is higher than 1.98).

1 Day Lag	S-Score				
Volume Rank	1,5	2	2,5	3	3,5
5	2,0331	2,0968	2,1791	1,7790	0,9953
10	2,5463	2,4603	2,6250	1,9788	1,3399
15	2,2857	2,2755	2,4654	1,3748	0,8125
20	1,8480	2,0557	2,2199	1,2460	1,2506
25	1,8573	2,0976	2,3046	1,2941	1,2519
50	2,4482	2,3789	2,0870	1,4867	1,1867
75	2,9984	3,2778	2,4736	1,2987	0,9025

Table 6.2 confirms the fact that alphas are still significant on strategies using several different inputs when regressing the second half of our returns. Table 6.3 shows that with an S-Score of 3 (extreme positive/negative sentiment regime), strategies loose significance when regressing only the last 6 months of the strategy's returns, which are not as good results as the ones yielded so far, but it must be taken into that an S-Score of 3 is an extreme sentiment regime and the period in analysis is short.

Information Ratio Analysis

"Information Ratio is the key to value added", by Grinold and Khan (2000). IR is widely used and it is a powerful tool to evaluate portfolio managers' skills. So that you can better evaluate information ratios present on table 7, Grinold and Kahn (2000) studied that an information ratio greater than 0 indicates that a portfolio manager has performed in the top 50% of the population, above 0.5 means that the manager performed in the top 75% of the population.

Table 7 – This table presents a sensitivity analysis on Information ratios resulting from strategies using different sentiment signals and volume filters, with 1 day lag.

1 Day Lag	S-Score				
Volume Rank	1,5	2	2,5	3	3,5
5	0,2277	0,2191	0,2352	0,2161	0,1953
10	0,1818	0,1836	0,1930	0,1770	0,1920
15	0,1565	0,1691	0,1839	0,1676	0,1794
20	0,1496	0,1603	0,1748	0,1539	0,1644
25	0,1448	0,1577	0,1724	0,1452	0,1643
50	0,1135	0,1471	0,1603	0,1278	0,1548
75	0,0901	0,1015	0,1209	0,1127	0,1425

The above table allows to conclude that managers using signals for sentiment would perform above average, and strategies using S-Scores of 2.5 and volume filters for 5 stocks have best ratios. This level for sentiment is in line with previous analysis, but the volume filter is not. If keeping the S-Score fixed while increasing the number of stocks of the volume filter, it is possible to observe a stable annualized return and a steadily decreasing annualized volatility. Taking this into account, and looking at the IRs above 0.2, allows to conclude that although the volatility of excess returns is lower (resulting in high IR), this is only achieved with high levels of volatility on portfolio's returns. A possible reason to explain the above analysis is that there are optimal levels for volume filters, and a number of stocks in which we want to invest, that increase levels of diversification on the portfolio and consequently increasing a unit of return per unit of risk – which is in line with previous analysis.

General Sentiment on S&P 500 Index

Another example of a strategy that was done using only signals for sentiment, was to take into account the average of sentiment of all stock in an index, an average sentiment of the S&P 500: if the average sentiment is >0 the investor decides to go long on the index, and in case the average is <0 the investor goes short. This strategy yields a Sharpe ratio of 0.8516, outperforming the index by an annualized return of 1.82% over the 3 years of the sample (8.90% vs 7.08%), with lower levels of volatility (10,45% vs 12.90%). Although these are interesting results, this series of returns is not statistically different from zero, and the regression with the Carhart model tells us that none factor or the alpha is significant:

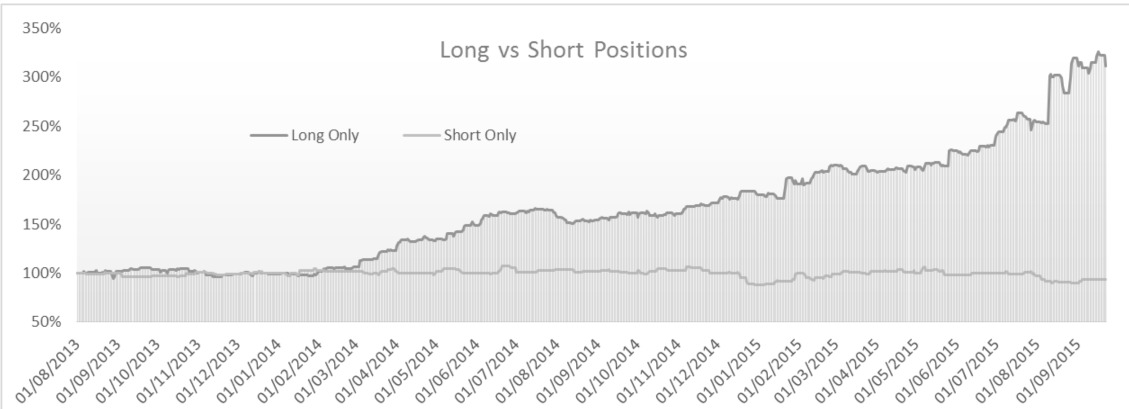
Table 8 - This table shows the coefficients, alpha and their significant, of the regression with the portfolio returns that takes into account the average sentiment of the S&P500 Index, with the Carhart model.

Carhart	MOM	HML	SMB	MKT	Alpha
Coefficient	0,0871	0,1152	0,0008	-0,0305	0,0508%
t-statistic	1,4962	1,2435	0,0131	-0,8070	1,6901

Different reactions on positive vs negative news

One final remark regarding this work's conclusions has to do with the fact that it is widely believed that people react more aggressively to negative news, compared to reactions on positive news. On Chart 2 you can see a decomposition of returns resulting from long and short positions on our base strategy, showing that the most relevant part of returns is coming from taking long positions derived from positive sentiment signals. Further analysis was not done on a long-only portfolio, since it was proved in an early stage that returns were not statistically different from zero and alphas were also not robustly significant.

Graph 2 – This graphs presents the decomposition of cumulative returns yielded from long positions vs short positions of our base strategy.



VI. Conclusion and Future Directions

"Using Twitter to track the mood of nations is analogous to using satellites to track the atmosphere", (Dodds, 2011).

Information allows investors to outperform their benchmark and differentiates active from passive portfolio management, and this work tries to prove that by analyzing millions of tweets it is possible to extract information that maximizes portfolios' performance relative to a specified benchmark by increasing investors' stock picking ability.

This work's results appear to support the hypothesis role of investor sentiment in behavioral finance, which has origin from a unique set of factors for sentiment and volume provided by Social Market Analytics Inc. that were used to build an investment strategy. The strategy is proved to have a positive and significant alpha in and out of sample with Fama-French and Carhart models regressions. These results add evidence of the powerful insights that can be extracted from social media sentiment to maximize profits, by improving investors' stock picking skills. From these results, we can also make inferences on the possibility that social media can be used in other areas of study such as business and health.

Regarding sentiment analysis, and the tool used to extract sentiment from Twitter, this work proves that SMA does it with success. The research that was done to work on this project allows one to believe that the sentiment analysis is only good if, when applied, shows positives outcomes, such as this strategy's results.

The data sample is short and it does not include an aggravated period of crisis. A greater set of data would increase the power of the analysis. Therefore, my suggestion would be to repeat the same study over a longer period of time. Also, an interesting analysis would be to add other factors such as the popularity of the user posting the Tweet, and a measure for unusual volume activity, which is believed to increase the powerful of the analysis.

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